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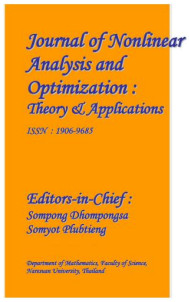


IDENTIFYING CYBER SECURITY THREATS IN FINANCIAL INSTITUTIONS WITH AI AND MACHINE LEARNING

[1]S. Venkat Rao,[2]Mr A.D.Sivarama Kumar
[1]Student,[2]Assistant Professor
Department Of CSE
SVR Engineering College, Nandyal

ABSTRACT

The increasing interconnectedness of digital assets is leading to an unparalleled surge in cyber attacks. Investments in artificial intelligence-based solutions are necessary if financial institutions are to recognize these dangers and safeguard their assets. When examining intricate financial security risks that are dynamic and often unpredictable, machine learning is a potent tool. Through the use of artificial intelligence (AI) technology, such as automated reasoning systems, natural language processing, and algorithms, banks may enhance their comprehension of possible hazards and establish more effective data controls. This study proposes a machine learning technique to identify cyber security concerns in financial institutions using artificial intelligence. Algorithms for machine learning are always being enhanced to find data abnormalities that might point to a security risk. With this strategy, financial institutions may use custom-made models that provide actionable insights into both internal and external threats to detect and fight against harmful assaults.

I. INTRODUCTION

1.1 General Introduction:

Financial fraud refers to the use of fraudulent and illegal methods or deceptive tactics to gain financial benefits. Fraud can be committed in different areas of finance, including banking,insurance,taxation,andcorporates,and more.Fiscal fraud and evasion, including credit card fraud, tax evasion, financial statement fraud, money laundry, and other types of financial fraud, has become a growing problem. Despite efforts to eliminate financial fraud, its occurrence adversely affectsbusinessandsocietyashundredsofmillion sofdollars are lost to fraud each year. This significant financial loss has dramatically affected individuals, merchants, and banks.

Nowadays, fraud attempts have increased drastically, which makes fraud detection more important than ever. The Association of Certified Fraud Examiners (ACFE) has announced that 10% of incidents concerning white-collarcrimeinvolvesfalsificationoffinancialstatements.They classifiedoccupationalfraudintothreetypes:asset misappropriation, corruption, and financial statement fraud. Financial statementfraudresultedinthemostsignificantlosesamong them.

Although the occurrence frequency of asset misappropriation and corruption is much higher than financial statement fraud, the financial implications of these latter crimes are still far less severe. In particular, as reported in a survey fromEisnerAmper,whichisamongtheprominent accounting firms in the U.S., ‘‘the average median loss of financial statement fraud ($800,000 in 2018) accounts for over three times the monetary loss of corruption

($250,000) and seven times as much as asset misappropriation ($114,000)''.

The focus of this study is on financial statement fraud. Financial statements are documents that describe details about a company, specifically their business activities and financial performance, including income, expenses, profits, loans, presumable concerns that may emerge later, and managerial comments on the business performance.

Allfirmsareobligatedtoannouncetheirfinancialstatements in a quarterly and annual manner. Financial statements can be used to indicate the performance of a company. Investors, market analysts, and creditors exploit financial reports to investigate and assess the financial health and earnings potentials of a business. Financial statementsconsistoffoursections;incomestatement, balance sheet, cash flow statement, and explanatory notes. The income statement places a great emphasis on a company's expenses and revenues during a specific period. The company's profit or net income is provided in this section,whichsubtractsexpensesfromrevenues.

Thebalance sheet provides a timely snapshot of liabilities, assets, and stockholders' equity. The cash flow statement measures the extent to which a company is successful in making cash to fund its operating expenses, fund investments, and pay its debt obligations. Explanatory notes are supplemental data that provide clarification and further information about particular items published financial statements of a company.

These notes cover areas including disclosure of subsequent events, asset depreciation, and significant accounting policies, which are necessary disclosures that demonstrate the amounts reported on the financial statements. Financial statement fraud involves falsifying financial statements to pretend the company more profitable than it is, increase the stock prices, avoid payment of the taxes, or get a bank loan.

Fraud triangle in auditing is a framework to demonstrate the motivation behind an individual's decision tocommitfraud. The fraud triangle has three elements that increase the risk of fraud: incentive, rationalization, and opportunity, which, together, lead to fraudulent behavior. Auditing professionals have extensively used this theory to explain the motivation behind an individual's decision to commit fraud.

It is indispensable to understand the fraud triangletoevaluatefinancialfraud. Guptaand Singh suggested that when there are incentives such as the obligation to achieve an outcome or cover losses, the potential for fraud increases. The company will encounter temptations or pressures to adopt fraudulent practices.

Moreover, the lack of inspections or unsuccessful controls provides a favourable occasion for committing fraud. Rationalization happens when the fraudster aims to justify the fraudulent action, and it could be affected by the others and the conditions.

Objectives:

The main objective of our project is,

- To predict or to classify the fraud and non-fraud data from financial statements.
- To implement the machine learning algorithm.
- To enhance the performance analysis.

1.2 Problem Statement:

Fraud detection refers to the problem of **finding patterns in data that do not conform to expected behavior**. These nonconforming patterns are often referred to as fraud, outliers, discordant observations, exceptions, aberrations, surprises, peculiarities, or contaminants in different application domains.

II. LITERATURE SURVEY:

Evaluation of financial statements fraud detection research: A multidisciplinary analysis, 2019

Author*:* A. Albizri, D. Appelbaum, and N. Rizzotto

Methodology

Prior research in the fields of accounting and information systems has shed some light on

the significant effects of financial reporting fraud on multiple levels of the economy. In this paper, we compile prior multi-disciplinary literature on financial statement fraud detection. Financial reporting fraud detection efforts and research may be more impactful when the findings of these different domains are combined. We anticipate that this research will be valuable for academics, analysts, regulators, practitioners, and investors.

Advantages:

- Reduced Manual power
- Low cost

Disadvantages:

- Too Many False Negatives.
- Run to failure prediction is low.

Interpretable fuzzy rule-based systems for detecting financial statement fraud, 2019

Author*:* P. Hajek

Methodology

Systems for detecting financial statement frauds have attracted considerable interest in computational intelligence research. Diverse classification methods have been employed to perform automatic detection of fraudulent companies. However, previous research has aimed to develop highly accurate detection systems, while neglecting the interpretability of those systems. Here we propose a novel fuzzy rule-based detection system that integrates a feature selection component and rule extraction to achieve a highly interpretable system in terms of rule complexity and granularity. Specifically, we use a genetic feature selection to remove irrelevant attributes and then we perform a comparative analysis of state-of-the-art fuzzy rule-based systems, including FURIA and evolutionary fuzzy rule-based systems. Here, we show that using such systems leads not only to competitive accuracy but also to desirable interpretability. This finding has important implications for auditors and other users of the detection systems of financial statement fraud.

Advantages:

- Avoid the over fitting from the dataset.

Disadvantages:

- It can be intimidating.

An application of ensemble random forest classifier for detecting financial statement manipulation of Indian listed companies, 2019

Author*:*H. Patel, S. Parikh, A. Patel, and A. Parikh

Methodology

A rising incidents of financial frauds in recent time has increased the risk of investor and other stakeholders. Hiding of financial losses through fraud or manipulation in reporting and hence resulted into erosion of considerable wealth of their stakeholders. In fact, a number of global companies like WorldCom, Xerox, Enron and number Indian companies such as Satyam, Kingfisher and Deccan Chronicle had committed fraud in financial statement by manipulation. Hence, it is imperative to create an efficient and effective framework for detection of financial fraud. This can be helpful to regulators, investors, governments and auditors as preventive steps in avoiding any possible financial fraud cases. In this context, increasing number of researchers these days have started focusing on developing systems, models and practices to detect fraud in early stage to avoid the any attrition of investor's wealth and to reduces the risk of financing.

In Current study, the researcher has attempted to explore the various 42 modeling techniques to detect fraud in financial statements (FFS). To perform the experiment, researcher has chosen 86 FFS and 92 non-fraudulent financial statements (nonFFS) of manufacturing firms. The data were taken from Bombay Stock Exchange for the dimension of 2008-2011. Auditor's report is considered for classification of FFS and Non-FFS companies. T-test was applied on 31 important financial ratios and 10 significant variables were taken in to consideration for data mining techniques. 86 FFS and 92 non-FFS during 2008-2017 were taken for testing data set. Researcher has trained the model using data sets. Then, the trained model was applied to the testing data

set for the accuracy check. Random forest gives best accuracy. Here, modified random forest model was developed with improved accuracy.

Advantages:

- Change of detecting unknown prediction.
- Fraud Detection more efficient than frauddetection, if fraud detection file is large.

Disadvantages:

- Run to failure prediction is low.
- Reliability is unclear.

Detecting fraudulent financial statements for the sustainable development of the socio-economy in China: A multi-analytic approach, 2019

Author*:* J. Yao, Y. Pan, S. Yang, Y. Chen, and Y. Li

Methodology

Identifying financial statement fraud activities is very important for the sustainable development of a socio-economy, especially in China's emerging capital market. Although many scholars have paid attention to fraud detection in recent years, they have rarely focused on both financial and non-financial predictors by using a multi-analytic approach. The present study detected financial statement fraud activities based on 17 financial and 7 non-financial variables by using six data mining techniques including support vector machine (SVM), classification and regression tree (CART), back propagation neural network (BP-NN), logistic regression (LR), Bayes classifier (Bayes) and K-nearest neighbor (KNN). Specifically, the research period was from 2008 to 2017 and the sample is companies listed on the Shanghai stock exchange and Shenzhen stock exchange, with a total of 536 companies of which 134 companies were allegedly involved in fraud. The stepwise regression and principal component analysis (PCA) were also adopted for reducing variable dimensionality. The experimental results show that the SVM data mining technique has the highest accuracy across all conditions, and after using stepwise regression, 13 significant variables were screened and the classification accuracy of almost all data mining techniques was improved. However, the first 16 principal components transformed by PCA did not yield better classification results. Therefore, the combination of SVM and the stepwise regression dimensionality reduction method was found to be a good model for detecting fraudulent financial statements.

Advantages:

- Rate of missing report is low.
- Simple and Effective method.

Disadvantages:

- Needs to be trained, and trained model carefully otherwise tends to be false positive.
- Low Accuracy rate.

An Analysis on Financial Statement Fraud Detection for Chinese Listed CompaniesUsing Deep Learning, 2020

Author*:* Wu Xiuguo, Du Shengyong

Methodology

Financial fraud has extremely damaged the sustainable growth of financial markets as a serious problem worldwide. Nevertheless, it is fairly challenging to identify frauds with highly imbalanced dataset because ratio of non-fraud companies is very high compared to fraudulent ones. Intelligent financial statement fraud detection systems have therefore been developed to support decision-making for the stakeholders. However, most of current approaches only considered the quantitative part of the financial statement ratios while there has been less usage of the textual information for classifying, especially those related comments in Chinese. As such, this paper aims to develop an enhanced system for detecting financial fraud using a state-of-the-art deep learning models based on combination of numerical features that derived from financial statement and textual data in managerial comments of 5130 Chinese listed companies' annual reports. First, we construct financial index system including both financial and non-financial indices that previous researches usually excluded. Then the textual

features in MD&A section of Chinese listed company's annual reports are extracted using word vector. After that, powerful deep learning models are employed and their performances are compared with numeric data, textual data and combination of them, respectively. The empirical results show great performance improvement of the proposed deep learning methods against traditional machine learning methods, and LSTM, GRU approaches work with testing samples in correct classification rates of 94.98% and 94.62%, indicating that the extracted textual features of MD&A section exhibit promising classification results and substantially reinforce financial fraud detection.

Advantages:

- Flexibility, fault tolerance, high sensing fidelity, low-cost and rapid deployment.

Disadvantages:

- Sensor nodes are prone to failures.

III. SYSTEM ANALYSIS

EXISTING SYSTEM:

Fraudulent financial statements (FFS) are the results of manipulating financial elements by overvaluing incomes, assets, sales, and profits while underrating expenses, debts, or losses. To identify such fraudulent statements, traditional methods, including manual auditing and inspections, are costly, imprecise, and time-consuming. Intelligent methods can significantly help auditors in analyzing a large numberoffinancialstatements.Inthisstudy,wesystematicallyreviewandsynthesizetheexistingliterature on intelligent fraud detection in corporate financial statements. In particular, the focus of this review is on exploring machine learning and data mining methods, as well as the various datasets that are studied for detecting financial fraud. We adopted the Kitchenham methodology as a well-defined protocol to extract, synthesize, and report the results. Accordingly, 47 articles were selected, synthesized, and analyzed.We presentthekeyissues,gaps,andlimitationsintheareaoffrauddetectioninfinancialstatementsandsuggest areas for future research. Since supervised algorithms were employed more than unsupervised approaches like clustering, the future research should focus on unsupervised, semi-supervised, as well as bio-inspired and evolutionary heuristic methods for fraud (fraud) detection. In terms of datasets, it is envisaged that futureresearchmakinguseoftextualandaudiodata.Whileimposingnewchallenges,thisunstructureddata deserves further study as it can show interesting results for intelligent fraud detection.

DISADVANTAGES:

- The results is low when compared with proposed.
- Time consumption is high.
- Theoretical limits.

PROPOSED SYSTEM:

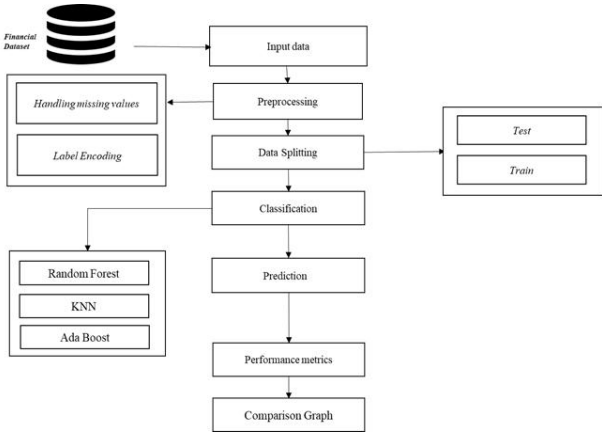
In our proposed system, we detect the fraud in financial statements by using the machine learning algorithm. First, we select and view the imported dataset for future purpose. And we get missing values and fill the default values to the dataset. We encoding the label in the dataset. And we split the dataset to the Train and Test data for predict the fraud or non-fraud. Then we use three algorithms for more accuracy, prediction and which is more accurate value. There are Random forest algorithm, KNN classifiers and Ada-Boost Algorithm. Now, we fit the training data from the dataset. Then we predict the test dataset using training dataset. Then the test values get the results of actual and predicted. And we get the performance of the dataset.It is essential to train the models on data which includes fraud and relevant non fraud. By using the ML algorithm the system is, to classify thefraud and non-fraud and results shows that the accuracy, precision, recall and f1-score and also prediction.This shows that method used in this project can predict the possibility of fraud accurately in most of the cases. This module is the simple and effective way to avoid such frauds and save those expenditures.

ADVANTAGES

- It is efficient for large number of datasets.
- The experimental result is high when compared with existing system.
- Time consumption is low.
- Provide accurate prediction results.

IV. SYSTEM DESIGN

SYSTEM ARCHITECTURE:



V. SYSTEM IMPLEMENTATION

MODULES:

- Data selection
- Data preprocessing
- Data splitting
- Classification
- Prediction
- Performance Metrics
- Graph Comparison

MODULES DESCRIPTION:

DATA SELECTION:

- The input data was collected from the dataset repository like UCI Repository.
- In this process, the input data have some columns like step, type, amount, nameOrig, balanceOrig, nameDest, balanceDest, isFlagged Fraud, etc.

In our collected dataset was read in this process using pandas.

DATA PREPROCESSING:

- Data pre-processing is the process of removing the unwanted data from the dataset.
- Pre-processing data transformation operations are used to transform the dataset into a structure suitable for machine learning.
- This step also includes cleaning the dataset by removing irrelevant or corrupted data that can affect the accuracy of the dataset, which makes it more efficient.
- Missing data removal
- Missing data removal: In this process, the null values such as missing values and Nan values are replaced by 0.
- Missing and duplicate values were removed and data was cleaned of any abnormalities.
- Label Encoding: In this process, the string values are converted into integer for more prediction.

Data Splitting

- During the machine learning process, data are needed so that learning can take place.
- In addition to the data required for training, test data are needed to evaluate the performance of the algorithm but here we have training and testing dataset separately.
- In our process, we have to divide as training and testing.
- Data splitting is the act of partitioning available data into two portions, usually for cross-validator purposes.
- One Portion of the data is used to develop a predictive model and the other to evaluate the model's performance.

Classifications

Random Forest Algorithm

- **Random forest** is a machine learning algorithm for fraud detection. It's an unsupervised learning algorithm that identifies fraud by isolating outliers in the data.

- Random Forest is based on the Decision Tree algorithm. It isolates the outliers by randomly selecting a feature from the given set of features and then randomly selecting a split value between the max and min values of that feature.
- This random partitioning of features will produce shorter paths in trees for the fraud data points, thus distinguishing them from the rest of the data.
- Random Forest isolates fraud in the data points instead of profiling non fraud data points. As fraud data points mostly have a lot shorter tree paths than the normal data points, trees in the isolation forest does not need to have a large depth so a smaller max_depth can be used resulting in low memory requirement.

KNN Algorithm:

- K-Nearest Neighbour is one of the simplest Machine Learning algorithms based on Supervised Learning technique.
- K-NN algorithm assumes the similarity between the new case/data and available cases and put the new case into the category that is most similar to the available categories.
- K-NN algorithm stores all the available data and classifies a new data point based on the similarity. This means when new data appears then it can be easily classified into a well suite category by using K- NN algorithm.
- K-NN algorithm can be used for Regression as well as for Classification but mostly it is used for the Classification problems.
- K-NN is a non-parametric algorithm, which means it does not make any assumption on underlying data.
- It is also called a lazy learner algorithm because it does not learn from the training set immediately instead it stores the dataset and at the time of classification, it performs an action on the dataset.
- KNN algorithm at the training phase just stores the dataset and when it gets new data, then it classifies that data into a category that is much similar to the new data.

Ada Boost Algorithm:

- AdaBoost also called Adaptive Boosting is a technique in Machine Learning used as an Ensemble Method. The most common algorithm used with AdaBoost is decision trees with one level that means with Decision trees with only 1 split. These trees are also called Decision Stumps.
- AdaBoost is best used to boost the performance of decision trees on binary classification problems.
- AdaBoost was originally called AdaBoost.M1 by the authors of the technique Freund and Schapire. More recently it may be referred to as discrete AdaBoost because it is used for classification rather than regression.
- AdaBoost can be used to boost the performance of any machine learning algorithm. It is best used with weak learners. These are models that achieve accuracy just above random chance on a classification problem.
- The most suited and therefore most common algorithm used with AdaBoost are decision trees with one level. Because these trees are so short and only contain one decision for classification, they are often called decision stumps.

Prediction

- Predict the dataset values are Non Fraud/Fraud by using classification algorithm.

Performance Metrics

The Final Result will get generated based on the overall classification and prediction. The performance of this proposed approach is evaluated using some measures like,

- **Accuracy:** Accuracy of classifier refers to the ability of classifier. It predicts the class label correctly and the accuracy of the predictor refers to how well a given predictor can guess the value of predicted attribute for a new data.

  AC= (TP+TN)/ (TP+TN+FP+FN)

- **Precision:** Precision is defined as the number of true positives divided by the number of true positives plus the number of false positives.

  Precision=TP/ (TP+FP)

- **Recall:** Recall is the number of correct results divided by the number of results that should have been returned. In binary classification, recall is called sensitivity. It can be viewed as the probability that a relevant document is retrieved by the query.

  Recall=TP/ (TP+FN)

- **F1-score:** F1 score of the positive class in binary classification or weighted average of the F1 scores of each class for the multiclass task. When true positive + false positive == 0, precision is undefined. When true positive + false negative == 0, recall is undefined.

  F1-score= 2*((precision*recall)/ (precision+recall))

Graph Comparison:

- Comparison between 3 algorithms for accuracy and prediction.

VI. SAMPLE SCREENSHOTS

DATA SELECTION:

```
#--------------------Data Selection--------------#
********************
```

	step	type	amount	...	newbalanceDest	isFraud	isFlaggedFraud
0	1	PAYMENT	NaN	...	0.00	0	0
1	1	PAYMENT	1864.28	...	0.00	0	0
2	1	TRANSFER	NaN	...	0.00	1	0
3	1	CASH_OUT	181.00	...	0.00	1	0
4	1	PAYMENT	11668.14	...	0.00	0	0
5	1	PAYMENT	7817.71	...	0.00	0	0
6	1	PAYMENT	7107.77	...	0.00	0	0
7	1	PAYMENT	7861.64	...	0.00	0	0
8	1	PAYMENT	4024.36	...	0.00	0	0
9	1	DEBIT	5337.77	...	40348.79	0	0
10	1	DEBIT	9644.94	...	157982.12	0	0
11	1	PAYMENT	3099.97	...	0.00	0	0
12	1	PAYMENT	2560.74	...	0.00	0	0
13	1	PAYMENT	11633.76	...	0.00	0	0
14	1	PAYMENT	4098.78	...	0.00	0	0
15	1	CASH_OUT	229133.94	...	51513.44	0	0
16	1	PAYMENT	1563.82	...	0.00	0	0
17	1	PAYMENT	1157.86	...	0.00	0	0
18	1	PAYMENT	671.64	...	0.00	0	0
19	1	TRANSFER	215310.30	...	0.00	0	0

DATA PREPROCESSING

Find Missing Values

```
#--------------------Find missing values--------------#
********************
step              0
type              0
amount            2
nameOrig          0
oldbalanceOrg     0
newbalanceOrig    0
nameDest          0
oldbalanceDest    0
newbalanceDest    0
isFraud           0
isFlaggedFraud    0
dtype: int64
```

Handling Missing values:

```
#--------------------Fill 0 from missing Values--------------#
********************
step              0
type              0
amount            0
nameOrig          0
oldbalanceOrg     0
newbalanceOrig    0
nameDest          0
oldbalanceDest    0
newbalanceDest    0
isFraud           0
isFlaggedFraud    0
dtype: int64
```

Label Encoding:

```
#--------------------Before Label Encoding--------------#
********************
```

	step	type	amount	...	newbalanceDest	isFraud	isFlaggedFraud
0	1	PAYMENT	0.00	...	0.00	0	0
1	1	PAYMENT	1864.28	...	0.00	0	0
2	1	TRANSFER	0.00	...	0.00	1	0
3	1	CASH_OUT	181.00	...	0.00	1	0
4	1	PAYMENT	11668.14	...	0.00	0	0
5	1	PAYMENT	7817.71	...	0.00	0	0
6	1	PAYMENT	7107.77	...	0.00	0	0
7	1	PAYMENT	7861.64	...	0.00	0	0
8	1	PAYMENT	4024.36	...	0.00	0	0
9	1	DEBIT	5337.77	...	40348.79	0	0
10	1	DEBIT	9644.94	...	157982.12	0	0
11	1	PAYMENT	3099.97	...	0.00	0	0
12	1	PAYMENT	2560.74	...	0.00	0	0
13	1	PAYMENT	11633.76	...	0.00	0	0
14	1	PAYMENT	4098.78	...	0.00	0	0
15	1	CASH_OUT	229133.94	...	51513.44	0	0
16	1	PAYMENT	1563.82	...	0.00	0	0
17	1	PAYMENT	1157.86	...	0.00	0	0
18	1	PAYMENT	671.64	...	0.00	0	0
19	1	TRANSFER	215310.30	...	0.00	0	0

```
#--------------------After Label Encoding--------------#
*******************
    step  type     amount  ...  newbalanceDest  isFraud  isFlaggedFraud
0      1     3       0.00  ...            0.00        0               0
1      1     3    1864.28  ...            0.00        0               0
2      1     4       0.00  ...            0.00        1               0
3      1     1     181.00  ...            0.00        1               0
4      1     3   11668.14  ...            0.00        0               0
5      1     3    7817.71  ...            0.00        0               0
6      1     3    7107.77  ...            0.00        0               0
7      1     3    7861.64  ...            0.00        0               0
8      1     3    4024.36  ...            0.00        0               0
9      1     2    5337.77  ...        40348.79        0               0
10     1     2    9644.94  ...       157982.12        0               0
11     1     3    3099.97  ...            0.00        0               0
12     1     3    2560.74  ...            0.00        0               0
13     1     3   11633.76  ...            0.00        0               0
14     1     3    4098.78  ...            0.00        0               0
15     1     1  229133.94  ...        51513.44        0               0
16     1     3    1563.82  ...            0.00        0               0
17     1     3    1157.86  ...            0.00        0               0
18     1     3     671.64  ...            0.00        0               0
19     1     4  215310.30  ...            0.00        0               0
```

DATA SPLITTING:

```
#--------------------Data Splitting--------------#
*******************

Total no of dataset : (80000, 11)
Training set Without Target (64000, 10)
Training set only Target (64000,)
Testing set Without Target (16000, 10)
Testing set only Target (16000,)
```

CLASSIFICATION:

```
#--------------------Random Forest Algorithm--------------#
*******************
Matrix:
[[15976     0]
 [   12    12]]
classfication:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00     15976
           1       1.00      0.50      0.67        24

   micro avg       1.00      1.00      1.00     16000
   macro avg       1.00      0.75      0.83     16000
weighted avg       1.00      1.00      1.00     16000

Accuracy:  99.925
```

```
#--------------------KNN Algorithm--------------#
*******************

Matrix:
[[15975     1]
 [   24     0]]
classfication:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00     15976
           1       0.00      0.00      0.00        24

   micro avg       1.00      1.00      1.00     16000
   macro avg       0.50      0.50      0.50     16000
weighted avg       1.00      1.00      1.00     16000

Accuracy:  99.84375
```

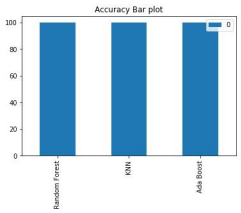
```
#--------------------Ada Boost--------------#
*******************
0.999

Matrix:
[[15973     3]
 [   13    11]]
classfication:
              precision    recall  f1-score   support

           0       1.00      1.00      1.00     15976
           1       0.79      0.46      0.58        24

   micro avg       1.00      1.00      1.00     16000
   macro avg       0.89      0.73      0.79     16000
weighted avg       1.00      1.00      1.00     16000

Accuracy:  99.9
```

PREDICTION:

```
#--------------------Get input from user--------------#
*******************

Enter the Step: 1

Enter the Type: 4

Enter the Amount: 0

Enter the nameOrig: 15121

Enter the oldbalance: 181

Enter the newbalance: 0

Enter the nameDest: 7874

Enter the oldbalance: 0

Enter the newbalance: 0

Enter the isFlaggedFraud: 0
[1]
This is financial Fraud
```

GRAPH:

```
#--------------------Camparision batween 3 Algorithm Accuracy--------------#
*******************
```



VII. CONCLUSION

In this project, we propose an approach to utilise the Random Forest algorithm, KNN and Adaboost algorithm for fraud detection in financial statements. We call the approach the three algorithms on datasets with significantly reduced dimensionality. The Classifications classifier gives high accuracy results that are comparable or superior to other fraud detection techniques in spite of working with reduced data and also compared with graph.

FUTURE ENHANCEMENT

In future, discovery of additional information based on cause-event Fraud detection well as prediction of detection based on cause events, etc.The working of the proposed approach in a web application.

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